Project: eems080
Pillar(s) Urban Science



U.S. DEPARTMENT OF ENERGY

SMARTMOBILITY

Systems and Modeling for Accelerated Research in Transportation

Typology of Cities for Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium

Paty Romero-Lankao National Renewable Energy Laboratory 2019 Vehicle Technologies Office Annual Merit Review June 11, 2019











OVERVIEW

Timeline

- Project start date: 12/01/19
- Project end date: 09/30/19
- Percent complete 30%

Budget

- Total project funding: \$300
 - DOE share: \$300
 - Contractor share: \$0
- Funding for FY 2017 \$0
- Funding for FY 2018 \$0

Barriers

- Barriers addressed
 - Cross city applicability of SMART mobility research findings
 - (https://energy.gov/eere/vehicles/usdrive-partnership-planroadmaps-andaccomplishments)

Partners

- LBLN, MEP, Cities LEAP, MIT, School of Mines, Oak Ridge, PenState
- PI: Paty Romero-Lankao













OVERVIEW

1. Enhance the value of SMART Mobility efforts by

 making relevant outcomes transferable among cities with similar characteristics

2. Create a multi-dimensional typology of adoption/impacts

- of emerging technologies in urban areas
- geographic information system (GIS)-based for reuse and sharing













RELEVANCE

Project objectives

- 1. Enhance the value of SMART Mobility efforts by making
 - Outcomes transferable among cities with similar characteristics
- 2. Create a multidimensional typology of adoption/impacts
 - GIS-based for reuse and sharing
 - Social, economic, technological, environmental and governance (SETEG) indicators relate with technology adoptions
 - Examine variations across settlements and status groups
- 3. Compare clustering methods and variables with similar geo-typology













RELEVANCE

Outcomes/Impact from AOP

- Clustering of cities and settlements by common characteristics for estimating national impact of automated, connected, efficient and shared transportation scenarios (NREL)
- Accessible data, analytics, and methods for SMART researchers and Cities partners on urban characteristics across many dimensions (NREL)
- Grouping of similar cities and settlements into a small (10 to 15) number of clusters (NREL)
- White paper of possible approaches and data to be used to create geotypes for FHWA project (LBNL)

AOP: Annual Operating Plan

FHWA: Federal Highway Administration

LBNL: Lawrence Berkeley National Laboratory NREL: National Renewable Energy Laboratory













MILESTONES

- First quarter (Q1) Urban data availability spreadsheet initial and & updated on an ongoing basis, indicating both available data and gaps
- Q3 Analytic tools of multi-layer urban data layers for SMART clustering analysis, integrated into Cities Leading through Energy Analysis and Planning (Cities-LEAP)
- Q4 –White paper and journal article summarizing the methods and findings of the clustering analysis











APPROACH

- 1. Analyze dimensions of urban areas
 - e.g., socioeconomic, technological
- 2. Build on/coordinate with existing efforts (Cities-LEAP, Mobility Energy Productivity [MEP], FHWA geotypology)
- 3. Conduct systemic literature review
- 4. Run factor analysis, cluster analysis, and correlations
- 5. Run Ordinary Least Squares (OLS) to examine links between population clusters/settlement type and adoption/impacts
- 6. Run sensitivity of geotypology results to alternative approaches and variables













APPROACH

Data SMART -> Cities-LEAP -> Robust Multi-Layer Typology Resource

Indicator	Туре	Domain	Source	Spatial level	Year
Total/group age	Independent	Social	American FactFinder	Census block	2016 5-Year
Total/group age	Independent	Social	American FactFinder	Census block	2016 5-Year
Gender	Independent	Social	American FactFinder	Census block	2016 5-Year
Education	Independent	Social	American FactFinder	Census block	2016 5-Year
Race	Independent	Social	American FactFinder	Census block	2016 5-Year
Median Income	Independent	Economic	American FactFinder	Census block	2016 5-Year
House tenure	Independent	Economic	American FactFinder	Census block	2016 5-Year
Vehicles per household	Independent	Economic	American FactFinder	Census block	2016 5-Year
Affordability: housing + transportat	Independent	Economic	CNT H&TA Index;	Census block	2015
Population density	Independent	Techno-infras	CNT H&TA Index;	Census block	2015
Residential density	Independent	Techno-infras	CNT H&TA Index;	Census block	2015
Employment access index (job den	Independent	Techno-infras	CNT H&TA Index;	Census block	2015
Intersection density	Independent	Techno-infras	CNT H&TA Index;	Census block	2015
Heating/cooling degree days	Independent	Environment	ftp://ftp.cpc.ncep.noaa.gov/htdocs/	degree_days/	2016
Carbon/energy intensity	Independent	Environment	https://www.eia.gov/environment/	Census block	2016
Air toxics respiratory hazard index	Independent	Environment	EPA EJS	Census block	2011
Hazard index (risk of) respiratory effec	Independent	Environment	EPA EJS	Census block	2011
Traffic proximity and volume:	Independent	Governance	EPA EJS	Census block	2014
Transportation mode choice	Independent	Governance	American FactFinder	Census block	2016 5-Year
Compactness	Independent	Governance	CNT H&TA index	Census block	2016 5-Year
EV adoption	Dependent		IHS Markit vehicle registration data	ZIP code	2017
Annual GHG per Household co2_pe	Dependent		CNT H&TA index	Census block	2015
Annual GHG per Acre autos_per_hl	Dependent		CNT H&TA index	Census block	2015
Diesel particulate matter level in air	Dependent		EPA EJS	Census block	2013
PM _{2.5} level in air	Dependent		EPA EJS	Census block	2011

EV: electric vehicle GHG: greenhouse gas













APPROACH

Typology: Dataset (20 indicators/9,405 census blocks)

		gender_fe			income_h	not_sov_c	tenure_ow		
blkgrp	total_pop	m	education	race_whi	h	om	n v	vehicl_hh l	nta_index
6.0014E+10	3018	0.5036448	0.65639496	0.72664016	177417	0.42516129	9 86	2.02	76
6.0014E+10	1105	0.46877828	0.64434389	0.80542986	166313	0.46241135	69	1.69	55
6.0014E+10	855	0.57192982	0.6619883	0.8	132400	0.60810811	L 58	1.59	54
6.0014E+10	1466	0.50886767	0.60163711	0.6255116	161964	0.39609644	1 61	1.66	60
6.0014E+10	1265	0.5083004	0.64110672	0.73438735	79375	0.60664112	2 36	1.42	43
6.0014E+10	985	0.56548223	0.32893401	0.46903553	29736	0.54095563	3 18	1.31	31
		intersect	compactn	e emplacci	e ghg hh e	s			

intersect_	compactne empl	_acce	ghg_	_hh_	_es
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pop dens hh	dens dens	SS	SS	t		diesel_pm ¡	om 25	cancer hazrespi haz		
437.750387	0.75	70	4.1	44078	8.09	0.7929689	_	3 1.7208835	• -	
3835.85991	6.32	385	7.2	68635	6.57	2.37348276	9.66278932	44.7120749	3.17394049	
2864.41757	5.17	381	8.1	71540	6.1	2.37348276	9.66278932	44.7120749	3.17394049	
5517.60477	7.42	380	7.5	70955	7.13	2.32813856	9.66012959	45.595051	3.22848943	
4696.54386	10.54	558	9.1	87745	4.88	2.32813856	9.66012959	45.595051	3.22848943	
3368.71913	7.61	674	9.6	84942		2.32813856	9.66012959	45.595051	3.22848943	













TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Correlation matrix shows links between

- Socioeconomic status (e.g., income) and urban form (e.g., compactness) indicators
- Urban form (e.g., population density) and impacts (e.g., emissions) indicators

	total_pop	gender_fem	education	race_whi	income_hh	not_sov_com	tenure_own	vehicl_hh	hta_index	pop_dens	hh_dens	intersect_dens	compactness	empl_access	ghg_hh_est	diesel_pm	pm_25	cancer_haz	respi_haz
total_pop		-0.04605	0.005088	-0.05208	0.125458	-0.049227	0.005607	0.090111	0.105123	0.040139	0.006462	-0.145727	-0.045533	-0.02557	0.153812	-0.038436	0.019324	-0.002167	-0.008102
gender_fem	-0.04605		0.03381	-0.08119	-0.052851	0.025521	-0.029461	-0.101573	-0.062806	0.059294	0.067219	0.068474	0.093391	0.028765	-0.116065	0.066789	0.048171	0.057687	0.050576
education	0.005088	0.03381		0.170862	0.683677	0.117766	0.159091	-0.08945	0.346604	0.100449	0.197285	0.096631	-0.003828	0.309816	-0.130457	0.195851	-0.040563	0.140972	0.171227
race_whi	-0.052084	-0.081189	0.170862		0.193051	-0.40593	0.432763	0.431457	0.394307	-0.335788	-0.256958	-0.423329	-0.517865	-0.198322	0.46275	-0.379822	-0.23432	-0.380475	-0.382988
income_hh	0.125458	-0.052851	0.683677	0.193051		-0.05954	0.474285	0.251799	0.626837	-0.040949	-0.008787	-0.091396	-0.315522	0.121759	0.26962	0.005323	-0.040244	-0.040741	0.011912
not_sov_com	-0.049227	0.025521	0.117766	-0.40593	-0.05954		-0.469026	-0.725501	-0.369583	0.639692	0.600975	0.542039	0.529683	0.579614	-0.699454	0.658607	-0.008248	0.489811	0.484528
tenure_own	0.005607	-0.029461	0.159091	0.432763	0.474285	-0.469026		0.700778	0.667048	-0.408676	-0.374836	-0.444292	-0.824974	-0.304185	0.715158	-0.41355	-0.101833	-0.430652	-0.381265
vehicl_hh	0.090111	-0.101573	-0.08945	0.431457	0.251799	-0.725501	0.700778		0.595674	-0.713266	-0.696761	-0.680815	-0.811554	-0.659059	0.910232	-0.776796	-0.129526	-0.636789	-0.584092
hta_index	0.105123	-0.062806	0.346604	0.394307	0.626837	-0.369583	0.667048	0.595674		-0.346862	-0.319424	-0.426726	-0.646048	-0.212792	0.591818	-0.371404	-0.062308	-0.348543	-0.322297
pop_dens	0.040139	0.059294	0.100449	-0.33579	-0.040949	0.639692	-0.408676	-0.713266	-0.346862		0.930948	0.557963	0.461727	0.619754	-0.641157	0.732003	0.063918	0.526557	0.495465
hh_dens	0.006462	0.067219	0.197285	-0.25696	-0.008787	0.600975	-0.374836	-0.696761	-0.319424	0.930948		0.530329	0.428219	0.688356	-0.627122	0.730552	0.051528	0.522295	0.483405
intersect_dens	-0.145727	0.068474	0.096631	-0.42333	-0.091396	0.542039	-0.444292	-0.680815	-0.426726	0.557963	0.530329		0.689206	0.451886	-0.672012	0.612497	0.209592	0.555184	0.530962
compactness	-0.045533	0.093391	-0.003828	-0.51787	-0.315522	0.529683	-0.824974	-0.811554	-0.646048	0.461727	0.428219	0.689206		0.401357	-0.822979	0.568066	0.21119	0.584827	0.549043
empl_access	-0.02557	0.028765	0.309816	-0.19832	0.121759	0.579614	-0.304185	-0.659059	-0.212792	0.619754	0.688356	0.451886	0.401357		-0.599811	0.74297	0.09686	0.57552	0.512128
ghg_hh_est	0.153812	-0.116065	-0.130457	0.46275	0.26962	-0.699454	0.715158	0.910232	0.591818	-0.641157	-0.627122	-0.672012	-0.822979	-0.599811		-0.717773	-0.151386	-0.623342	-0.584495
diesel_pm	-0.038436	0.066789	0.195851	-0.37982	0.005323	0.658607	-0.41355	-0.776796	-0.371404	0.732003	0.730552	0.612497	0.568066	0.74297	-0.717773		0.243496	0.758219	0.744125
pm_25	0.019324	0.048171	-0.040563	-0.23432	-0.040244	-0.008248	-0.101833	-0.129526	-0.062308	0.063918	0.051528	0.209592	0.21119	0.09686	-0.151386	0.243496		0.326911	0.216271
cancer_haz	-0.002167	0.057687	0.140972	-0.38048	-0.040741	0.489811	-0.430652	-0.636789	-0.348543	0.526557	0.522295	0.555184	0.584827	0.57552	-0.623342	0.758219	0.326911		0.806066
respi_haz	-0.008102	0.050576	0.171227	-0.38299	0.011912	0.484528	-0.381265	-0.584092	-0.322297	0.495465	0.483405	0.530962	0.549043	0.512128	-0.584495	0.744125	0.216271	0.806066	

Note: This is this is not a regression yet. Red and green are negative and positive correlations, respectively. The darker shades are only stronger or weaker correlations, not statistical significance.









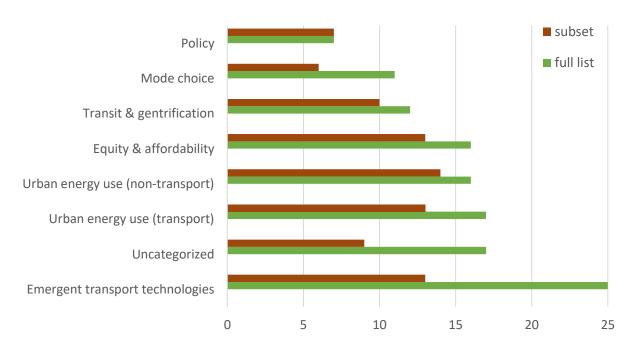




TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Focus on multi-dimensional determinants (e.g., urban form) and impacts (e.g., on mobility and energy) of emergent technologies

Systemic Review: Publications by Category















RESPONSES TO PREVIOUS YEAR'S REVIEWERS' COMMENTS

• This project is new for FY 2019.













COLLABORATION AND COORDINATION WITH OTHER INSTITUTIONS

- NREL-LBNL collaborations seeking to
 - Compare applicability to freight transport of clustering methods
- Typology MEP collaborations seeking to
 - Use MEP as dependent variable in typology regression
- Typology Cities-LEAP collaborations seeking to
 - Consider Cities-LEAP assets and visualization tools
 - Design in the future a buildings and transportation typology











COLLABORATION AND COORDINATION WITH OTHER INSTITUTIONS

- Typology New York collaborations to
 - Apply typology to GIS analysis of adoption of emergent transport technologies and its energy impacts
- Typology Massachusetts Institute of Technology (MIT) collaborations seeking to
 - Compare and contrast MIT and NREL methodologies
 - Use MIT data archive as an example
- Typology Colorado School of Mines collaborations to
 - Refine replicability of statistical methods
- Typology PenState/Western State University collaborations (still in the making) seeking to
 - Respond to DOE VTO \$59M funding opportunity.













REMAINING CHALLENGES AND BARRIERS

- We are looking for other and more accurate indicators of energy use and emissions by transport at a finer level of resolution – e.g., block census level
- We lack appropriate transportation infrastructure and mobility behavior data layers













PROPOSED FUTURE RESEARCH

If we are successful with the typology,

- Can we identify subunits in urban areas that are consistent across different cities, independent of the difference between the cities as a whole?
- Can understanding of-what happens within the subunits help inform difficulties in the adoption of efficient transportation technologies? E.g., in accommodating energy sources that are intermittent or at risk from weather extremes and cyber-attacks?
- Can this typology help to provide tools to project adoption scenarios across these subunits?

Any proposed future work is subject to change based on funding levels.





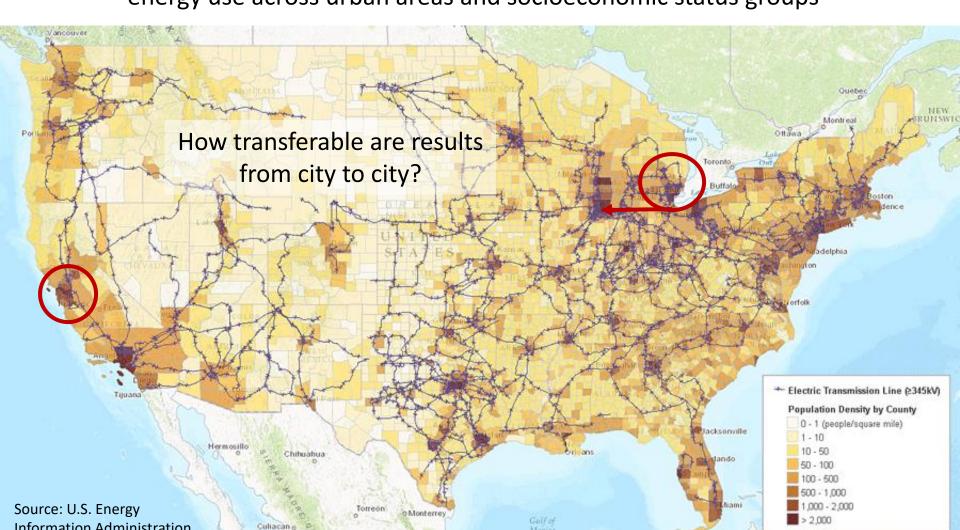




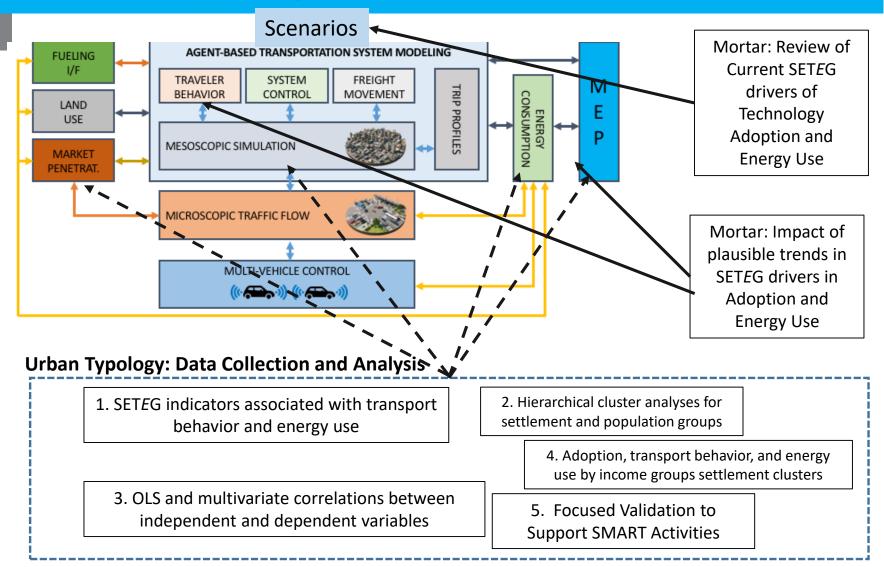


SUMMARY

Typology to identify clusters of features in emergent transportation behavior and energy use across urban areas and socioeconomic status groups



Urban Typology Mapping to SMART End-to-End Workflow – Additional Supporting Tasks















PUBLICATIONS AND PRESENTATIONS

- Abstract was accepted to present this typology at the International Conference on Energy and Social Science in Phoenix
- The PI was invited to give a keynote on the Transformative Potential of Emergent Technologies at The "2019 Transformations Conference" in Santiago de Chile
- We intend to publish a paper to circulate internally with LBNL in a high-impact journal
- Incorporate FHWA comments into geotypology white paper and circulate externally (including with NREL) for peer review (LBNL)













CRITICAL ASSUMPTIONS AND ISSUES

 This effort presents a snapshot approach to typologies. In the future, we will combine clustering with time series and scenarios to represent the dynamic nature of our typology.

























